DISCIPLINING DELEGATED MONITORS: EVIDENCE FROM VENTURE CAPITAL*

Xuan Tian
Department of Finance
Kelley School of Business
Indiana University
tianx@indiana.edu

Gregory F. Udell
Department of Finance
Kelley School of Business
Indiana University
gudell@indiana.edu

Xiaoyun Yu
Department of Finance
Kelley School of Business
Indiana University
xiyu@indiana.edu

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Abstract

Information-based theories of financial intermediation focus on delegated monitoring. However, there is little evidence on how markets discipline financial intermediaries who fail at this function. This paper uses the venture capital (VC) market to address this gap in the empirical literature by looking at how VC's reputations are affected when they fail in their monitoring role to prevent fraud by their portfolio firms. We find that VCs who fail to prevent fraud experience greater difficulty in taking future portfolio firms public, and that the negative effect prevails over ten years after the fraud surfaces. In addition, reputation-damaged VCs interact differently in the future with their limited partners, other VCs in the community, and their IPO underwriters because they are perceived by these groups as inefficient monitors.

Key Words: Corporate Fraud, Venture Capital, Reputation, Financial Intermediaries, Corporate Governance, Initial Public Offerings

JEL Classification: D01, D85, G2, G24, G3, K4

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1. INTRODUCTION

Modern information-based theories of financial intermediation emphasize information production as the *raison d'être* for financial intermediaries (e.g., Diamond 1984, Ramakrishnan and Thakor 1994, Boyd and Prescott 1986). Subsequent theory has built on this foundation to explain why some firms access the private markets while others access the arms length public securities market (e.g., Rajan 1992). This work is based on the notion that financial intermediaries generate soft information about their customers through their screening and monitoring activities. A key implication of this literature is that firms who are opaque need the costly information production services provided by financial intermediaries in the private markets. The empirical literature on financial intermediation generally confirms that opaque firms tend to access private intermediated markets while transparent firms are more likely to access the public securities markets (e.g., Carey et al. 1993, Hadlock and James 2002).

Substantially unanswered in the literature, however, is the issue of how well do financial intermediaries perform this information production function. More specifically: How do markets discipline financial intermediaries that fail in their delegated responsibility to produce information about potential and existing borrowers? This is a very difficult question to answer for several reasons. First, as is generally the case with testing information-based theories, the empiricist is typically denied access to the private soft information that lies at the heart of the model being tested. That is, empirical tests of information models are generally indirect because the empiricist does not get to directly observe the soft information (or lack of soft information) produced by the financial intermediary. Second, the best place for the empiricist to look for evidence of screening and monitoring efficiency is in the segment of the market where firms are the most informationally opaque because that is where information production is most important. This implies that the best place to analyze how financial intermediaries are disciplined is in the small and mid-sized enterprise (SMEs) sector where firms are dependent on financial intermediaries for external financing. Unfortunately, in most countries the SME market is the worst place for an empiricist to look due to a paucity of data.[1] This is a particularly acute problem in the U.S. where there is relatively little data on SMEs because the U.S. does not have a public credit registry—unlike, for example, Argentina, Italy, and Spain.[2]

We substantially overcome these problems by looking at evidence from the venture capital market on monitoring performance. In many ways venture capital is the canonical form of financial intermediation. Like banks, venture capital firms very much act as delegated monitors. Venture capital firms obtain funding from limited partners and redeploy it by investing in start-up firms—the VC firm's "portfolio firms". These portfolio firms are highly opaque and the monitoring intensity is likely greater than in any other intermediated market. These features of the venture capital market make it an ideal place to study financial intermediation. In addition, the venture capital market is substantially unregulated and thus not "polluted" (as an economic experiment) by government regulation and government guarantees. But one other feature of this market offers us a unique opportunity to examine how markets discipline financial intermediaries that fail to monitor adequately. While we can't observe VC monitoring effort directly, we can observe *ex post* some of the most egregious monitoring failures in this market. Specifically, we are able to observe VC portfolio firms that are the subject of securities fraud lawsuits immediately after going public. We argue that the essence of monitoring is to mitigate an agency problem between insiders and outsiders. Insiders have an incentive to misrepresent their quality and the nature of their behavior. Fraud is, in effect, a strong form of misrepresentation. Our empirical strategy in this paper is to examine the consequences from the damage to a VC's reputation from the failure to monitor sufficiently and prevent incipient fraudulent behavior.

To evaluate the economic consequences faced by a VC after being revealed as an ineffective monitor, we use a sample of VC-backed U.S. firms that went public during the 1995 to 2005 period and were detected for fraud. We follow the literature and measure detected fraud

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[1] Empirical evidence confirms that smaller firms tend to be more financially constrained and that they are more dependent on the contracting technologies that can mitigate information problems including the production of soft information (e.g., Beck, Demirguc-Kunt and Maksimovic 2006, and Gopalan, Udell and Yerramilli 2010).

[2] Arguably the best available data on SMEs in the U.S. is the Federal Reserve's Survey of Small Business Finance. This has been used in many papers to study SME external financing (e.g., Petersen and Rajan 1994, 1995, Berger and Udell 1995, Berger et al. 2005). Unfortunately, this survey was only conducted four times and was terminated by the Federal Reserve Board just prior to the onset of the financial crisis. Moreover, the survey does not provide panel data nor does it reveal the identity of the firms which substantially limits its usefulness in studying the topic in this paper.

with securities lawsuits alleging accounting-related fraud during the period leading up to two years after the IPO.

We find evidence that the market does indeed discipline VCs for lack of sufficient monitoring, as VC firms appear to suffer reputational damage from the failure to prevent IPO fraud. First, these VC firms are less likely to harvest subsequent portfolio investments through IPOs which are otherwise their most attractive exit mechanism. In choosing the exit venue of their investments, they also tend to substitute the IPO exit with a much less profitable exit pathway such as mergers and acquisitions (M&As). More importantly, the negative effect of monitoring failure on VC firm's future exit and the exit choice is persistent, showing no signs of decay even after ten years after the discovery of fraud committed by their portfolio firms.

Second, reputation-damaged VCs appear to suffer in their future interaction with other players in VC market. Specifically, they interact differently in the future with their limited partners, other VCs in the community, and their IPO underwriters because they are perceived by these groups of peers as inefficient monitors. Reputation-damaged VC firms have to commit to a more conservative investment strategy by restricting their subsequent investments to fewer industries and more local entrepreneurial firms. When interacting with other VCs in the subsequent ventures, reputation-damaged VC firms have to join a smaller VC syndicate and team up with lower reputable syndicate members. For subsequent IPOs, they tend to work with underwriters with lower reputation rankings relative to their earlier IPO underwriters.

Lastly, we find evidence that markets assign a different magnitude of discipline depending on the extent of the interactions between a VC and its fraudulent portfolio firms. The reputational damage due to VC's monitoring failure is much more pronounced among VCs who begin their investment at the early stage of their portfolio firms, and therefore, who have the most extensive involvement with these fraudulent firms. In addition, the market does not appear to be consistently more tolerant—and VC takes less blame—if the general business conditions are more prone for the incidence of fraud.

There has been relatively little empirical literature on disciplining delegated monitors. Dahiya, Saunders and Srinivasan (2003) and Gopalan, Nanda, and Yerramilli (2010) focus on commercial lending by banks. They found that banks incur loss in their market value and experience difficulty to syndicate loans in the future, respectively, when their borrowers suffer financial distress.[3] Different from these studies, we identify an event that is directly linked to monitoring, rather than being confounded by other functions performed by financial intermediaries, which allows us to explicitly examine how monitoring failure contributes to the damage in their reputation.[4] In this respect, our study is related to Lin and Paravisini (2010) who study the effect of the discovery of fraud on the reputation of commercial banks in the loan syndication market. However, our study differs from Lin and Paravisini (2010) by examining an industry setting (i.e., the VC market) which is free from the confounding effects of intense government regulation and government guarantees. Furthermore, by studying how VCs who fail to monitor interact with other financial intermediaries in subsequent deals, the VC market allows us to explore a much broader range of effects from reputation damage beyond just the flow of future deal funding including, for example, the creditors of the intermediary itself.

Our paper is also related to the large literature studying the role of VC investments in the value creation for entrepreneurial firms. The literature has shown that value creation arises from VC's intensive monitoring (Barry et al. 1990, and Lerner 1995), reputation (Nahata 2008, and Krishnan et al. 2010), industry expertise (Gompers, Kovner, and Lerner 2009), staged investment structure (Gompers 1995 and Tian 2010), syndication (Lerner 1994a, Brander, Amit, and Antweiler 2002, and Tian 2009), market timing ability (Lerner 1994b), and network positions (Hochberg, Ljungqvist, and Lu 2007). Instead of examining how VCs' investments affect their portfolio firms, we concentrate on the economic consequences associated with VC itself when it fails to perform the monitoring function. To the best of our knowledge, this is the first study analyzing through what mechanisms the markets discipline VCs for being effective monitors.

[3] Kracaw and Zenner (1996) also examined bank share price reactions to borrower distress but did not find a statistically significant effect.

[4] There are many explanations for the negative wealth effects on banks. While it is possible that the banks did not adequately monitor their borrower and intervene to mitigate the lending losses, the negative wealth effects could be attributable to the direct effect from the loss in the net present value of the relationship with the commercial borrower who got into distress. In addition, it could be that the loss in bank wealth is due to a contagion effect associated with exposure to other borrowers in the same sector. There is one empirical study that specifically analyzes how financial intermediaries attempt to assure that their employees monitor their commercial customers sufficiently (Udell 1989). And more broadly the relationship lending literature analyzes how monitoring ultimately benefits borrowers and what type of organizational form is best suited to deliver this monitoring (e.g., Petersen and Rajan 1994, Berger and Udell 1995, Stein 2002, Berger et al. 2005). This literature, however, does not address the issue of how the market disciplines financial intermediaries to insure that they monitor adequately.

Our findings thus shed light on why reputation constitutes the major concern of financial intermediaries.[5]

Finally, our paper is related to the empirical literature on corporate fraud. Researchers have identified factors that are linked to fraud incentive, such as equity compensation for executives (e.g., Burns and Kedia 2006, Efendi, Srivastava, and Swanson 2007, Peng and Röell 2008, and Johnson, Ryan, and Tian 2009), corporate boards lacking independence or financial and accounting expertise (e.g., Beasley 1996, Dechow, Sloan, and Sweeney 1996, Agrawal and Chadha 2005), and business conditions (Wang, Winton, and Yu 2010). Another strand of literature studies various mechanisms in detecting fraud (e.g., Beneish 1999, Francis 2004, Wang 2009, and Dyck, Morse, and Zingales 2010). Instead of corporate fraud per se, we use the discovery of the IPO fraud by its portfolio firms as a proxy for VC's lack of effective monitoring, and focus on how the revelation of monitoring failure affects the VC's interactions with capital markets and other financial intermediaries.

The rest of the paper is structured as follows. Section 2 describes the research design and estimation strategy. Section 3 discusses data sources and sample construction. In Section 4 we present our results on how reputation damage affects subsequent VC exits. In Section 5 we present our results on subsequent interactions between VCs who suffer reputation damage and their limited partners, VC peers, and underwriters. Section 6 contains the extensions of our analysis and robustness checks. Section 7 concludes.

2. RESEARCH DESIGN AND ESTIMATION STRATEGY

2.1 Proxies for Monitoring Failure in Venture Capital

Venture capital firms have expertise in creating value for entrepreneurial firms that have high growth potential but also significant uncertainty. They are actively involved in the entrepreneurial firm's business operations and developments. To obtain initial as well as follow-on rounds of capital infusions, the entrepreneurial firm is subject to extensive screening, advising, and monitoring from VC investors (Barry et al. 1990, Gompers 1995, Lerner 1995, Hellmann and Puri 2002, and Chemmanur, Krishnan, and Nandy 2009).

[5] Atanasov, Ivanov, and Litvak (2010) document negative wealth effect associated with VCs directly involved in litigations for conflict of interest with their portfolio firms. Instead of VC's private benefit, we concentrate on the reputation damage arising from a VC's failure to perform delegated monitoring role.

To isolate the monitoring role from other functions performed by VCs, we identify an event—the discovery of fraudulent activities by a VC-backed IPO firm. The incidence of fraud indicates the negligence or ineffectiveness of VC monitoring, which in turn, leads to potential damage in VC reputation.

VC's involvement with a portfolio firm does not terminate immediately after the firm goes public. Gompers and Lerner (1998) find that VC investors cash out about 70% of their investment in an IPO firm within two years after the IPO. To capture the presence of a VC firm during the fraudulent period of its portfolio company, we classify a fraud committed by VC-backed firm as an IPO fraud if it is committed during the period leading up to two years after the IPO.

The discovery of a securities fraud generally leads to a securities lawsuit. There are two types of securities lawsuits: the SEC's Accounting and Auditing Enforcement Releases (AAERs) and private securities class action lawsuits. Many papers have used lawsuits to proxy for the presence of corporate financial fraud (e.g., Beasley 1996, Beasley, Carcello, and Hermanson 1999, Helland 2004, Srinivasan 2005, Fich and Shivdasani 2007, Peng and Röell 2008, Wang, Winton, and Yu 2010). We therefore follow the literature and measure detected fraud with securities lawsuits alleging accounting-related fraud during the IPO process and up to two years after IPO.[6]

Our first proxy for a VC's monitoring failure is "IPO Fraud", a dummy that equals one if at least one of the portfolio companies backed by the VC had committed fraud within two years after it went public and zero otherwise. Our second proxy reflects the severity of the IPO fraud, measured as the three-day cumulative abnormal announcement period return (CAR) surrounding the discovery of the fraud. Intuitively, severity of fraud suggests significance in monitoring failure, and leads to greater damage in VC reputation. Specifically, we define "Fraud Severity" as a variable that equals two if the three day CAR is more negative than the median CAR, one if

[6] In the corporate fraud literature, one issue of using lawsuits as a proxy for fraud is the false detection. As discussed in Section 3.1, we follow the standard filtering procedures to rule out false detection. In addition, this issue is less a concern in the context of our research: Generally speaking, a class action lawsuit, even if frivolous, generates negative publicity for the defendant firms and the financial intermediaries involved. In the absence of negative publicity, mis-classification of fraud works against finding any results.

the three day CAR is less negative than the median CAR, and zero if no frauds are detected in the IPO firm financed by the VC firm.[7]

2.2 Evaluating the Economic Consequences of VC Monitoring Failure

2.2.1 Probability of Future Successful Exit

We analyze the economic consequences faced by VCs who were present during the period when their portfolio companies committed fraud. Our first set of measures, the probability of successful exit by the VC who suffers reputation damage, attempts to capture how investors perceive the quality of subsequent portfolio companies brought by the same VC to the market.

There are generally three possible venues through which a VC firm can exit its investments: an IPO, the sale of a portfolio company to a third party (merger and acquisition), and a write-off. Among these the IPO is the most profitable venue of exit for the VC industry (Sahlman 1990 and Brau, Francis, and Kohers 2003). In particular, Brau, Francis, and Kohers (2003) show that IPO firms enjoy a 22% "valuation premium" relative to firms that are acquired, and Sahlman (1990) argues that most returns for VC investors are earned on companies that eventually go public.

Although mergers and acquisitions (M&As) tend to generate smaller returns for VCs than IPOs, they are still profitable and are widely considered as one of the two successful exit venues (e.g., Brander, Amit, and Antweiler 2002, Hochberg, Ljungqvist, and Lu 2007, Chemmanur and Loutskina 2008, Nahata 2008, and Gompers, Kovner, and Lerner 2009). In the event of a write-off, the VC firm liquidates its portfolio firm and bears a loss in its investment.

We define "IPO Exit" as a dummy that equals one if in a given year a VC-backed portfolio firm goes public (thus the VC exits its investment via an IPO), and zero if it is acquired or written off. Since VCs can cash out of their investments via more than one venue, it is possible that a VC who suffers reputation damage could compensate for its diminished exit opportunity through the IPO venue by pursuing the second best (but still generally quite profitable) alternative via an M&A and thus, still achieving a high overall gain on its investments. To account for this, we defined "Successful Exit" as a dummy variable equal to one if a VC exits its investment via either an IPO or an M&A and zero if the investment is written off.

[7] We do not use the actual return itself in this setting as in this case, the announcement return is non-existent for firms that are not detected fraud. Assigning zero to the announcement return to these firms leads to misinterpretation in a continuous variable framework.

Our third proxy further explores the potential substitution effect between an IPO exit and an M&A exit. Between both types of successful exits, we define "IPO vs. M&A" as a dummy variable equal to one if the exit is via an IPO and zero if via an M&A.

2.2.2 The Impact from Other Financial Intermediaries

Our second set of measures explores how other financial intermediaries and institutional investors interact in subsequent deals with a reputation-damaged VC after the discovery of fraud. We first examine the interaction between a VC and its limited partners who supply capital for subsequent investment opportunities. We postulate that after the revelations of fraud and a lack of VC monitoring before and during the IPO stage, VC firms become more conservative in response to the demand from existing and potential limited partners for more vigilant monitoring effort.

We measure the conservativeness of VC investment—and thus the intensity of its monitoring—by its industry and geographic concentrations. Since VCs typically specialize and concentrate their investment in a few industries, we capture a VC firm's industry concentration with its investment Herfindahl index as in Gompers, Kovner, and Lerner (2009). Specifically, the Herfindahl index equals the sum of the squares of the percentage of all investments (in terms of the number of entrepreneurial firms) in each of the 18 industries classified in the Venture Economics database in each of subsequent year.[8,9] We posit that VCs whose reputation is damaged by their previous fraudulent IPOs are forced by their limited partners to take on a more conservative investment strategy by concentrating their investments in fewer industries to facilitate their more intensive and effective monitoring.

The second set of measures that we use to capture the conservativeness of a VC's investment strategy is the locality of its subsequent portfolio firms. Our proxy "Ln(Distance)" is the natural logarithm of the weighted average physical distance between the VC firm and its portfolio firms, calculated using the great circle distance formula as in the existing studies. Alternatively, we compute "% of Local Investment" as the percentage of local investment within

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[8] The 18 industries assigned by the Venture Economics database are Agriculture/Forestry/Fish, Biotechnology, Business Services, Communications, Computer Hardware, Computer Other, Computer Software, Construction, Consumer-Related, Financial Services, Industrial/Energy, Internet-Specific, Manufacture, Medical/Health, Other, Semiconductor/Electronics, Transportation, and Utilities.

[9] We calculate an alternative Herfindahl index based on the funding amount in an industry and the results (not reported) are quantitatively unchanged.

a VC's portfolio. Local investment is defined as the investment in portfolio firms that are located within a 50-mile radius of the VC firm. Since the previous literature has documented that VC firms can less costly monitor their portfolio firms and perform better in local investments (e.g., Cumming and Dai 2010, and Tian 2010), we conjecture that in response to the demand by limited partners for more vigilant monitoring, VC firms whose reputation is damaged focus their subsequent investments on local ventures. As result, we should observe a decline in distance between these VCs and their portfolio firms, and a rise in local investment in VCs' portfolio after the discovery of the fraud.[10]

VCs tend to syndicate their investments with other VCs, rather than investing alone (Lerner 1994, Brander, Amit, and Antweiler 2002, and Tian 2009). We next explore how a VC interacts with other VCs in forming syndicates after the discovery of the fraud. We use syndicate size to capture the scale of investment, and the average reputation of other syndicate members to capture the quality of syndication. We postulate that for subsequent investment opportunities, VCs that are perceived as inefficient monitors by other VCs are likely to join syndicates of smaller size and pool with VCs that are less reputable than them.

For each VC firm, we construct the syndicate size of each of its subsequent investments by counting the number of other VCs within the syndicate across all financing rounds. "Ln(# of VCs)" is then calculated as the natural logarithm of the average syndicate size across all subsequent investments in each of the subsequent years.

Next, we measure the quality of other VC investors within a syndicate by calculating the weighted average of VC reputation. For each VC firm, we follow Nahata (2008) and Bhattacharya, Borisov, and Yu (2010) and compute VC reputation based on an extended window for a given year as the fraction of total proceeds of IPOs that are financed by the VC since 1980. Using 1980 instead of the beginning year of our sample alleviates the potential forward-looking bias. Alternatively, we follow Krishnan et al. (2010) and compute VC reputation based on a rolling window for a given year as the fraction of total proceeds of IPOs that the VC has invested in the 3-year rolling window. For each VC firm who has backed an IPO firm that committed fraud, we then construct "High VC Reputation (Extended)" and "High VC Reputation (Rolling)," a dummy variable equal to one if the weighted average VC reputation based on extended

[10] Cumming and Dai (2010) argue that VCs exhibit strong local bias in their investments, while Tian (2010) shows that VC firms do invest in distant ventures. By contrast, we compare the locality of the portfolio firms backed by the same VC before and after the discovery of the fraud, instead of comparing the locality across different VCs.

window (rolling window) within the syndicates of the subsequent investments is higher than that of the VC, respectively.

In addition to limited partners and other venture capitalists, VCs also interact with underwriters (investment banks) when bringing their portfolio companies to public. Sherman (1999) predicts that underwriters generally have an incentive to screen out fraud so as to forestall legal liability and loss of reputation. Wang, Winton, and Yu (2010) find that lower underwriter monitoring costs are associated with less fraud overall. A natural extension of these studies would imply that an underwriter's concern about its reputation not only discourages IPO fraud through its intensive screening and monitoring, but also leads to reluctance to work with VCs who are inefficient monitors. For each VC, we compute an "IB Reputation", which we define as the weighted average reputation for the underwriting syndicate of any subsequent IPO deal. To directly capture whether VC reputation damage affects the pool of underwriters available to the VC for subsequent deals, we also compute "High IB Reputation", equal to one if the weighted average reputation for the underwriting syndicates in subsequent IPOs backed by the same VC is higher than the weighted average reputation of underwriting syndicates in its previous deals and zero otherwise. We postulate that VCs who are perceived as inefficient monitors are less likely to engage more highly reputable banks to underwrite their subsequent IPOs and, instead, are forced to work with less reputable underwriters relative to the pool of underwriters in their earlier IPOs.

3. DATA SOURCE AND SAMPLE CONSTRUCTION

3.1 Sample Construction

3.1.1 The IPO Fraud Sample

We extract the IPO issues from Thomson Financial SDC database. After excluding unit offers, rights offers, closed-end mutual funds, REITs, ADRs, and partnerships, our search of the SDC database yielded 1,391 VC-backed IPO issues between January 1995 and December 2005.

We use the filing of a securities lawsuit based on financial misreporting against an IPO firm as our proxy for detected IPO fraud. Since it takes roughly two years on average to discover fraud during this period (Wang, Winton, and Yu 2010), we extract a sample of fraudulent firms from the Stanford Law School's Securities Class Action Clearinghouse and the SEC's Accounting and Auditing Enforcement Releases (AAERs) filed between 1996 and 2007, with the fraud being committed between 1995 and 2005.

To control for frivolous lawsuits, we first restrict our sample to the period after the passage of the Private Securities Litigation Reform Act of 1995, which was designed to reduce frivolous lawsuits (e.g., Johnson, Kasznik, and Nelson 2000, and Choi 2007). We then follow Dyck, Morse, and Zingales (2009) and exclude all cases where the judicial review process leads to their dismissal. Third, for those class actions that have settled, we exclude those firms where the settlement is less than $2 million, a threshold level of payment suggested by previous studies that helps divide frivolous suits from meritorious ones (Grundfest 1995, and Choi, Nelson, and Pritchard 2005). To match the litigation nature of the SEC's AAERs, we identify the nature of the class action allegations based on the materials in all the available case documents associated with each lawsuit (i.e., case complaints, press releases, defendants' motion to dismiss, and court decisions) and single out cases involving allegations of accounting irregularities. This yields 423 SEC AAERs and 1,085 private class action lawsuits, among which 212 suits were subject to both SEC enforcement and private class action litigation.

We then merge our litigation sample with our VC-backed IPO sample. We check the timing of the alleged frauds based on the information in the litigation documents and identify 205 frauds occurred before or within two years after the IPO. We label these 205 cases as IPO Frauds. If a fraud is committed after a VC exits, we classify it as a Post-Exit Fraud. The 205 fraudulent portfolio firms have received funding from 196 unique VC firms before they exit through IPO.

3.1.2 The VC Sample

For each IPO fraud that is committed between 1995 and 2005, we examine the economic consequences for the associated VCs up to three years after the discovery of fraud. We extract data on portfolio firms and VC investment in these firms from the Thomson Venture Economics database during the 1995-2008 period. We exclude financial firms and those with missing or inconsistent data.

The Venture Economics database provides detailed information on the portfolio firm's development stage at the first VC investment round (i.e., startup/seed stage, early stage, expansion stage, later stage, and buyout/acquisition stage), the date the firm was established, the firm's industry classification, the identity of the investing VC firms, the date of each financing round, and the date and type of the eventual outcome for each portfolio firm, i.e., IPO, M&A, or write-off (defunct).[11] However, the database does not identify all firms that are eventually written off. Therefore, based on the fact that the VC industry requires investment liquidation within 10 years from the inception of a fund in the majority of the cases, we also classify a firm as a write-off if it did not receive any financing within a 10-year span after its last financing round.[12] All other firms that are not classified into one of the three categories (IPO, M&A, and write-off) are considered as the firms that are still under active investment by VC investors and therefore excluded from our sample.

The Venture Economics database also provides detailed information about the characteristics of VC firms. We compute the age of VC firms as the number of years since the VC firm's founding year. We also compute the amount of capital under a VC firm's management in a given year.

Our final sample consists of 11,500 unique portfolio firms that are backed by VCs and 1,682 unique VC firms from 1995 to 2008.

3.2 Descriptive Statistics

Table 1 Panel A reports summary statistics for VC firms and their portfolio firms in our sample during the sample period. Among 1,770 unique VCs that have taken at least one of their portfolio firms public during our sample period, 196 (11.1%) of them have funded a fraudulent IPO firm, and 154 (8.7%) of them have backed an IPO firm that committed fraud after their exit. Among the 205 frauds, we are able to identify the date when the fraud surfaces for 171 cases and compute the three-day cumulative abnormal announcement period return (CAR). The average CAR is -31.6%. A typical VC firm has an industry Herfindahl index of 0.55, and invests in portfolio firms that are on average 214 miles away. On average, a VC firm is 13.6 years old with $29.2 million capital under management.

Among 11,500 unique sample portfolio firms that have received VC financing, 9.6% of them achieve exit via an IPO during our sample period; 65.2%, or 7,500 portfolio firms, exit through either an IPO or an M&A. Among the 7,500 portfolio firms that achieve a successful

[11] We update and fill in the missing observations for the date that the portfolio firm was established. We use Jay Ritter's database (http://bear.cba.ufl.edu/ritter/ipodata.htm) for the subset of firms that went public and Factiva, LexisNexis, D&B, and CorpTech databases for firms remaining private.
[12] An alternative cut-off is used for classifying write-off firms if the entrepreneurial firm did not receive any follow-on financing within a 5-year span after its very last financing rounds. Results (not reported) are both quantitatively and qualitatively unchanged.

exit, 14.7% choose IPO instead of M&A exit. 62.6% of these firms receive VC financing at various early stages of their life cycle (seed stage, early stage, and expansion stage). For a typical portfolio firm in our sample, the average size of an investing VC syndicate is three.

Instead of VC firms and their portfolio companies for the entire sample, Table 1 Panel B reports the descriptive statistics for the 205 VC-backed fraudulent IPO firms. An average fraudulent firm receives funding from six VC syndicate members, and VC funding begins four years after the firm is founded.[13] More interestingly, 88% of these fraudulent firms receive VC financing at their seed stage, early stage, or expansion stage, with 66% of them begin to interact with VCs at their seed or early stage. This is in sharp contrast with the sample portfolio firms in general (Panel A), where only 25.6% of them receive VC funding at their seed or early stage. These findings suggest that VC's failure to prevent IPO fraud is more likely driven by its ineffective monitoring, as VCs are involved with these firms at the very beginning stage of their life cycle.

Table 1 Panel C compares the characteristics of VCs that have backed a fraudulent IPO firm during the sample period and those that have not. There is preliminary evidence that the failure to prevent IPO fraud by VC's portfolio companies is unlikely driven by the lack of VC's experience: Compared to VCs that have not funded fraudulent IPOs, VCs that have funded fraudulent IPOs tend to have invested in a significantly larger number of entrepreneurial firms, have participated in a significantly large number of financing rounds, and have enjoyed a considerably higher reputation (score), regardless of whether VC reputation is computed based on a three-year rolling window or an extended window. These VCs are also older and manage a larger amount of capital, though the difference is not statistically significant.

4. FAILURE TO MONITOR AND THE PROBABILITY OF FUTURE EXITS

4.1 Baseline Regressions

In this section we examine the impact of IPO fraud conducted by VC-backed firms on future exit venues of the VC firm in a probit regression framework. The sample consists of VC-backed firms that have achieved an exit during the sample period, so the unit of analysis is VC-

[13] Among the 196 VC firms that have financed the fraudulent IPOs, 38 of them play the lead VC role, and 20 of the lead VCs are involved with more than one fraudulent sample firm. For our main analyses, we do not distinguish among VCs funding one or more than one fraudulent firm. As the robustness checks in Section 6.4 indicate, this does not affect our main findings.

portfolio firm observations. To ensure the conservativeness of our analysis, we exclude portfolio firms backed by VCs that have never had an IPO exit—and, therefore, had never been exposed to reputation damage in the first place—during our sample period.

Table 2 Panel A reports the results. We report the marginal effects of independent variables because the coefficients of the probit model are usually hard to interpret. Since residual terms are correlated for portfolio firms backed by the same VC firm, heteroskedasticity-robust standard errors are clustered at the VC level and reported in parenthesis.

Column (1) of Table 2 Panel A investigates the relationship between IPO fraud by VC-backed firms and the probability of future exit via IPOs by the same VC. Specifically, the dependent variable is "IPO Exit", equal to one if the VC-backed firm goes public in a given year and zero if it is acquired or written off. The main variable of interest is the IPO fraud dummy. For each given year, this dummy variable is set to one if the VC that backs a given sample firm is revealed within the previous three years as a failed monitor, and zero otherwise. Varying the length of the period prior to a given year of exit from three years up to five years does not alter our findings.

Following Benvensite et al. (2003), we control for IPO waves—defined as the number of IPOs at the time of VC's portfolio firm exit. We follow the VC literature and control for VC characteristics such as VC firm's age at the time of the exit and natural logarithm of capital under VC firm's management as well as the characteristics of the portfolio firms, including the firm's development stage when it received the first round of VC financing.[14] In addition, we control for portfolio firm's industry fixed effects, where industries are based on Venture Economics 18-industry classifications.

We observe that after controlling for industry fixed effects, IPO waves, VC age, capital under management, and venture development stages, the IPO fraud dummy is negatively and significantly related to the probability of subsequent IPO exits. Compared to portfolio firms backed by VCs who are not inefficient monitors, these that are backed by VCs who suffer reputation damage are 35.9% less likely to go public within three years after fraud is detected. This suggests that investors are more reluctant to purchase shares of companies backed by the

[14] We include four development stage dummies in the regression, and the omitted group represents entrepreneurial firms that are at the buyout stage when it received the first round VC financing.

VC firm who are revealed to be ineffective monitors, and that these VCs face greater difficulty in exiting their subsequent investments via IPOs.

Column (2) of Table 2 Panel A confirms the results in Column (1), where we use a different proxy for the degree of monitoring failure by VCs—"Fraud Severity." The marginal effect of fraud severity is negative and significant at the 1% level, suggesting that the more severe the fraud committed by VC-backed IPO firms, the lower probability of subsequent VC's portfolio firms exit via IPOs.

Although IPO is the most profitable venue of exit, it is not the only successful exit channel for venture capitalists. While the investors in the public markets may be reluctant to purchases shares of portfolio companies backed by VCs who suffer reputation damage, it is possible that VCs are able to sell their ventures to a third party (e.g., other companies). As a result, VCs who are revealed to be ineffective monitors could still achieve positive returns by substituting more M&A exits for IPO exits. To test this hypothesis, we replace the IPO exit dummy with the "Successful Exit" dummy for the dependent variable in Columns (3) and (4) of Table 2 Panel A, where the successful exit dummy equals one for either an IPO *or* an M&A exit and zero for a write-off exit.

Columns (3) and (4) reveal that IPO fraud dummy and fraud severity are negatively and significantly related to the probability of future successful exit, respectively. For example, the marginal effect of IPO fraud dummy in Column (3) suggests that VC investors who have previously backed firms that committed IPO fraud are 21.8% less likely to bring their portfolio companies to public or sell their portfolio firms in the subsequent three years. Together with Columns (1) and (2), these findings suggest that damage to a VC's reputation is not limited to IPO exits, but extends to both of the successful exit pathways.

Nevertheless, there is an implication in these results that VCs who fail to monitor tend to substitute IPO exits with a less attractive exit in harvesting subsequent investments, as the marginal effects of the IPO fraud dummy and Fraud Severity tend to be smaller for future successful exit than for just the first best exit strategy via an IPO. For example, VCs who have previously backed firms that committed IPO fraud are 21.8% less likely to achieve a successful exit within three years after the fraud surfaces (Column (3)), which is much smaller than the 35.9% reduction in the probability of just the first best exit via an IPO (Column (1)). The substitution of an M&A exit for an IPO exit also reflects the damage to a VC's reputation.

In Columns (5) and (6) we explicitly investigate whether VCs substitute the more profitable IPO exit with the less profitable M&A exit by focusing on the subsample of portfolio firms that have successfully exited. The dependent variable in the probit regression is a dummy equal to one if the VC exits its subsequent investment via an IPO, and zero if via an M&A. We observe that both the IPO fraud dummy and fraud severity are negatively and significantly related to the probability of future exists via an IPO. For example, VCs who have previously backed firms that committed IPO fraud are 27% less likely to pursue an IPO exit in favor of an M&A exit.

When estimating the probability of exit (Table 2 Panel A) using the probit regressions, we follow the literature and control for the characteristics of VC firms and of their portfolio companies as well as industry fixed effects. However, it is possible that portfolio companies backed by VCs that suffer reputation damage are systematically different from those backed by VCs that do not. We are unable to include VC firm's fixed effects due to the fact that the estimations with VC fixed effects do not converge in the non-linear probit model. More importantly, our tests aim at comparing exit outcomes between VC firms that suffer reputation damage and those that do not; including VC firm fixed effect largely subsumes the comparison itself. Nevertheless, to ensure the robustness of our results, we estimate a linear probability model with VC firm's fixed effects included instead.

Table 2 Panel B reports the results.[15] We observe that, similar to Panel A, both IPO fraud dummy and fraud severity are negatively related to future IPO exits and successful exits, and within successful exits, both IPO fraud dummy and fraud severity are negatively related to IPO exit over M&A exit. This suggests that controlling for VC fixed effects, portfolio firm's industry fixed effects, VC age at the time of exit, the amount of capital under management at the time of exit, and the stage of the portfolio firm, firms backed by VCs that suffer reputation damage are less likely to exit after the fraud surfaces. The dummy for IPO fraud is significant at the 1% or 10% levels, albeit the fraud severity variable is no longer statistically significant.[16]

[15] We would like to caution the interpretation of the results in Table 2 Panel B, as the usual caveats common to using the linear probability model with binary dependent variables apply here. While the linear probability model generally tends to give qualitatively correct effect of independent variables on dependent variables, the coefficient estimates and standard errors are likely to be biased. Therefore, the results obtained from the linear probability model should be treated only as suggestive evidence.

[16] The lack of statistical significance would be driven by a significant loss of degree of freedom in the linear probability model when VC firm's fixed effects are included.

To summarize, the results in Table 2 indicate that VC firms who fail to monitor their portfolio companies effectively will subsequently face greater difficulty in achieving successful exits. In addition, there is a shift in the choice of exit venues once a VC's reputation is damaged: instead of pursuing the more profitable IPO exit for their subsequent investments, these VCs opt for the less profitable exits via an M&A.

4.2 The Persistence of the Impact of Reputation Damage on Future Exits

How long do the markets hold unfavorable view of VCs being ineffective monitors? To recycle their "informed capital," venture capitalists repeatedly harvest their portfolio companies in the public or private markets (Michellaci and Suarez 2004). If the "institutional memory" of market participants fades quickly, then the negative impact of reputation damage is at most temporary.

We now explore the persistence of the impact of VC reputation damage on future exits by estimating the probit regressions on a yearly basis as follows: The dependent variable is a dummy equal to one if there is an exit of a VC-backed firm in year $t + i$, where year t is when an IPO firm previously backed by the same VC was detected for fraud. Since the VC industry usually requires investment liquidation within 10 years from the inception of a fund, we vary i from 0 up to 10. Table 3 reports the results. For brevity, only the results for year t, $t + 1$, $t + 2$, $t + 3$, $t + 5$, and $t + 10$ are presented. The results for the rest of years are similar and hence are not tabulated.

The dependent variable in Panel A of Table 3 is the IPO exit dummy. Our regressions show that both the IPO fraud dummy and fraud severity are negatively and significantly related to the probability of an IPO exit in each of the subsequent years. More importantly, there is no evidence of decay in institutional memory, as the marginal effect for these variables remains very similar in magnitude from year t through year $t + 10$.

In Panel B, we replace the dummy for an IPO exit with the dummy for a successful exit in the probit regressions. We observe that the marginal effects of the IPO fraud dummy are all negative and significant in each of ten years subsequent to the IPO fraud detection. The magnitudes of these marginal effects remain almost identical across years. Taken together, these findings suggest that the effect of reputation damage on VC future exits lasts as long as ten years after the discovery of the fraud, and that the institutional memories of investors in both IPO markets and M&A markets are not short term.

Lastly, the dependent variable in Panel C of Table 3 is replaced with the IPO vs. M&A dummy. Our regression results suggest that among successful exits, VCs who are inefficient monitors are more likely to exit through M&As rather than IPOs. More importantly, the marginal effect for IPO fraud dummy and fraud severity remain almost unchanged from year t through year $t + 10$. The substitution effect between the two profitable venues of exit also persists over a relatively long period of time.

5. PRESSURE FROM OTHER MARKET PLAYERS

In the previous section we find evidence that VC firms who are perceived as ineffective monitors suffer greater difficulty in bringing their portfolio firms public or selling them to a third party. In this section, we investigate how their subsequent investments and interactions with various market players are affected by their reputation damage. Specifically, we posit that reputation-damaged VCs suffer "peer pressure" from their limited partners, other VCs in the community, and underwriters.

5.1. Peer Pressure from Limited Partners

To pursue investment opportunities, VCs interact with various players in the capital markets. Limited partners, from whom VCs raise capital, are substantially drawn from a major group of players in the capital markets (e.g., commercial banks, corporate and public pension funds, insurance companies, and endowments). The role of limited partners in the day-to-day operations of the VC firm is restricted by law if they are to retain limited liability. Hence, it is difficult for limited partners to evaluate the VC's abilities and performance, forcing them to substantially rely on the observed outcomes of a VC's previous ventures. Gompers (1996) shows that the size of a VC firm's next fund depends on the number of IPOs it has financed previously. Therefore, once a VC's current (and potential future) limited partners observe direct evidence of its lack of effective monitoring (e.g., the fraud in a VC's previously financed IPO firm surfaces), concerns arise about the VC's ability to monitor in the future. Thus, limited partners may require VCs who suffer reputation damage to increase the intensity of monitoring for subsequent investments in return for supplying subsequent capital. Consequently, a reputation-damaged VC may have to commit to a more conservative investment strategy in the future.

We measure monitoring intensity with "Industry Concentration" and "Locality." As described in Section 2, "Industry Concentration" is a VC firm's investment Herfindahl index based on Venture Economics 18-indsutry classifications, and "Locality" is captured by the natural logarithm of physical distance between the VC firm and its portfolio firms, as well as the percentage of local investment in a VC's portfolio. To examine how failure to monitor affects monitoring intensity for subsequent investments, we regress the degree of industry concentration and locality on the IPO fraud dummy and fraud severity, respectively. We control for time-varying VC Age and capital commitment by limited partners, measured by the natural logarithm of total capital under VC management, as well as the VC firm's prior performance, measured by the "successful" exit rate of its portfolio firms in the previous three years. We include VC firm fixed effects to absorb any VC time-invariant characteristics that may affect its subsequent investments and year fixed effects to control for calendar-time fixed effects, which accounts for variations over time associated with market movements that may influence VC's investment behavior.

Table 4 reports the regression results for industry concentration (Panel A) and locality (Panel B), respectively. Heteroskedasticity-robust standard errors clustered at VC firm level are reported in parenthesis. We observe that controlling for VC age, capital commitment, past performance, and VC firm and year fixed effects, both the IPO fraud dummy and fraud severity are positively and significantly related to the degree of industry concentration for VC's subsequent investments. For example, a VC firm increases its industry Herfindahl index by 0.082, a 14.9% (=0.082/0.55) increase based on the mean value of the Herfindahl index, upon a detection of fraud by its previously financed IPO firms. This result is consistent with the hypothesis that VC investors who previously fail to monitor effectively tend to invest more conservatively by concentrating on a fewer number of industries in order to improve their monitoring efficiency in subsequent ventures.

In Panel B of Table 4, we report the regression results where the dependent variable is the natural logarithm of physical distance between VC firms and portfolio firms (Columns (1) and (2)), and the percentage of local investment in a VC firm's portfolio (Columns (3) and (4)). Controlling for year and VC fixed effects, the coefficient estimates of both the IPO fraud dummy and Fraud Severity are negatively and significantly linked to the distance between VC firm and its portfolio firms, and are positively and significantly linked to the percentage of local investment in its portfolio. For example, the magnitude of the IPO fraud dummy suggests that a VC firm tends to invest in ventures that are 15.1% closer to its current location upon a detected fraud of its previously financed IPO firms. Our evidence suggests that in order to monitor ventures more effectively, VCs who suffer reputation damage pursue investment opportunities that are physically closer to them in distance.[17]

5.2. Peer Pressure from VC Peers

When pursuing investment opportunities, VCs often form syndicates. If VCs are concerned about their reputation as well as returns, they will be reluctant to team up with a VC who is known as a poor monitor. This might force a reputation-damaged VC to syndicate with lower quality VCs in the future. To evaluate the subsequent syndicate quality of reputation-damaged VCs, we first regress the size of VC syndicates on an IPO fraud dummy and fraud severity, respectively, for investments made after the discovery of fraud.

Table 5 Panel A reports the results. We observe that controlling for VC age, capital commitment, past performance, and VC firm and year fixed effects, the IPO fraud dummy (Column (1)) and fraud severity (Column (2)) are negatively and significantly linked to the size of VC syndicates. This evidence suggests that VCs who previously backed a fraudulent IPO firm have to join smaller syndicates in their subsequent investments. For example, the coefficient estimate of the IPO fraud dummy suggests that the syndicates that a VC joins for subsequent investments are 8.9% smaller upon the discovery of fraud committed by its previously financed IPO firms.

Next, in Panels B and C, we replace the dependent variable with an indicator variable that equals one if the weighted average reputation of other VCs in the syndicate is higher than the VC's own reputation and zero otherwise. This analysis captures the reputation of other VCs with whom the VC firm teams up. Since the dependent variable in the probit model is an indicator variable measuring the reputation of a VC relative to the average reputation of its VC peers, we

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[17] Our findings suggest that VC's failure to monitor is likely to generate negative externalities to its limited partners with a less diversified investment opportunity set. Since VC investments are highly industry-specific and the demand for VC capital is high (Sahlman 1990), the shrinking in VC's investment scopes also potentially deprives young firms of a critical source of funding. While the issue on these two types of externalities is interesting, it is beyond the scope of this paper.

cannot include VC firm fixed effects as in Panel A. Instead, we include industry fixed effects to control for any variations that only vary across industries but cannot explain our main results. We report the marginal effects of independent variables because the coefficients of the probit model are usually hard to interpret.

Table 5 reports the regression results in which VC reputation is measured based on a three-year rolling window (Panel B) and an extended widow (Panel C) as described in Section 2, respectively. Controlling for VC age, capital commitment, past performance, year and industry fixed effects, the coefficient estimates of both the IPO fraud dummy (Columns (3) and (5)) and fraud severity (Columns (4) and (6)) are negative and significant, regardless of how VC reputation is measured. For example, the magnitude of IPO fraud dummy reported in Column (3) suggests that a VC whose previous IPO firms had fraud detected is 25.9% less likely to team up with VCs whose reputation is higher than its own reputation. The evidence suggests that reputation damage hurts a VC's ability to join a syndicate with members who more reputable. A reputation-damaged VC has to team up with poorer quality VCs in its subsequent deals.

In summary, the results in Table 5 suggest that for their subsequent investments, VCs suffering reputation damage as an ineffective monitor tend to join smaller syndicates and syndicates with less reputable VCs. "Peer pressure" from other VCs in the community represents another economic consequence of monitoring failure.

5.3. Peer Pressure from Underwriters

A VC firm not only interacts with its limited partners and other VCs, but it also interacts with underwriters when it takes its portfolio firms public. A large literature has established that investment banks have a gate-keeping role in the IPO process and that in discharging this role their reputation matters (e.g., Beatty and Ritter 1986, Carter and Manaster 1990, Chemmanur and Fulghieri 1994, and Fang 2005). As argued by Sherman (1999), taking a fraudulent firm public may have a very negative impact on an underwriter's reputation. Consequently, a reputable underwriter may be reluctant to take firms public that are backed by VCs who have been revealed to be poor monitors.

To examine whether a reputable underwriter is willing to work with reputation-damaged VCs, we first regress the underwriter reputation rank for subsequent IPO deals on the IPO fraud dummy and fraud severity, respectively. Table 6 Panel A presents the regression results.

Controlling for VC age, capital commitment, past performance, VC firm and year fixed effects, the IPO fraud dummy and fraud severity are negatively and significantly related to the weighted average reputation rank of underwriters involved in subsequent IPO deals backed by the same VCs. The evidence suggests that higher reputation underwriters are less willing to bring firms public backed by the VCs who are perceived as poor monitors.

In Panel B, we replace the dependent variable with an indicator variable that equals one if the current reputation of underwriters is higher than the average reputation of underwriters involved in the VC's earlier IPOs and zero otherwise. We estimate the regression using a probit model and report the marginal effects of independent variables. Similar to Panels B and C of Table 5, industry instead of VC firm fixed effects along with year fixed effects are included. The marginal effects of both the IPO fraud dummy and fraud severity are negative and significant. For example, the magnitude of the IPO fraud dummy in Column (3) suggests that a reputation damaged VC is 5.4% more likely to team up with less reputable underwriters (relative to its earlier IPO deals) when it brings its portfolio firms to public upon the detection of fraud of its previously financed IPOs.

6. EXTENSIONS AND ROBUSTNESS

6.1 Extent of VC Involvement with Fraudulent IPO Firms

When disciplining VCs for monitoring failure, those who have the most extensive involvement with the fraudulent IPO firms should suffer the most. We examine whether the market assigns a different magnitude of discipline depending on the extent of the interaction between VCs and their fraudulent portfolio firms.

We split the sample based on the stage of investment (i.e., earlier-stage and later-stage) in which the VC investor is specialized and re-estimate our regressions from Tables 2 through 6. The intuition behind this subsample analysis is that VCs who typically invest in earlier-stage ventures have a lengthier interaction with their portfolio firms and hence engage in in more protracted and intensive monitoring. On the other hand, VC investors who typically invest in later-stage ventures have a less intensive interaction with their portfolio firms and may be "excused" for a lack of intensive monitoring by market participants because of their limited involvement with a subsequently revealed fraud failure. Therefore, we expect the economic consequences of reputation damage to be more pronounced for VCs who are more responsible for intensive monitoring for their portfolio firms, i.e., earlier-stage VCs. We define a VC firm to be an earlier-stage VC if more than half of its past investment since 1980 is in seed, early, or expansion stages, and a later-stage VC if more than half of its past investment since 1980 is invested in ventures in later or buyout stages.

Table 7 reports the results. Panel A is for early stage VC firms, whereas Panel B is for late stage VC firms. For brevity, we only report the coefficient estimates of main interest variable, IPO fraud dummy, and suppress all other control variables. We observe that the marginal effect for investment exits (Columns (1) through (3) and Columns (7) and (8))) and the OLS coefficient estimates (Columns (4) and (5)) are uniformly larger for the IPO fraud dummy during early stage (Panel A) than during late stage VC investments (Panel B). They are also more statistically significant.

Consistent with our conjecture, Table 7 suggests that the economic consequences of monitoring failures are more pronounced for VC firms that have a higher monitoring responsibility.

Alternatively, we measure the extent of VC involvement in a fraudulent IPO firm as the ratio of a VC's average incubation period over average firm age at the time of the IPO.[18] The greater the ratio, the longer the VC stays with the firm. We then classify a VC as an early (late) VC if its ratio is above (below) the sample median and re-run Table 7 (untabulated). Note that a forward-looking bias emerges when the sample median instead of exogenous investment stage as in Table 7 is used to classify a VC's investment involvement; nevertheless, this classification provides a noisy alternative for the extent of VC involvement with its portfolio firms. We find similar results for VC exits and VC's interactions with other VC peers and underwriters for subsequent investments; the marginal effect for the IPO fraud dummy is larger if VC has more prolonged involvement with the fraudulent firms. The results for VC's investment scope and syndicate size, however, are weaker.

6.2 VC Expertise in Effective Monitoring

We have so far documented that VCs who fail to prevent fraud at pre-IPO and IPO stages suffer from more discipline, i.e., they suffer greater difficulty when they exit from their portfolio

[18] A VC's incubation period in a portfolio firm is defined as the time interval between its first investment date and the last investment date if the portfolio firm exits through M&A or write-off. For IPO firms, a VC's incubation period is defined as the time interval between its first investment date and the IPO date.

investments in the future, and face greater peer pressure for subsequent investments. Furthermore, the negative impact on a VC's failure to monitor is more pronounced when the VC has a longer period of involvement with a fraudulent firm before its IPO. However, we do not distinguish what causes the monitoring failure in the first place. A VC may not be able to prevent/detect fraud due to the lack of expertise in identifying fraudulent activities, or due to the presence of misaligned incentives.

In this subsection we explore whether the market distinguishes between failures arising from a lack of expertise vs. misaligned incentives. We postulate that preventing or detecting fraudulent activities by VC firms requires certain expertise. Often VC investments cluster around technological industries where start-up firm success is highly uncertain due to technical challenges. Therefore, it seems reasonable that the more uncertainty associated with an industry, the more the demand for monitoring expertise from the VC

To identify firms where VC's expertise is more important for effective monitoring, we construct an industry-wide variable "Technical Uncertainty" based on patent filings of firms in the entire Compustat Universe during the 1994-2006 period. We obtain patent filing information from the National Bureau Economic Reseaerch (NBER) patent database. Following the innovation literature, we correct for the truncation problems in the NBER patent database and set the patent numbers to zero for firms that have no patent information available from the NBER database.

For each Compustat firm during the 1994-2006 period, we regress its Tobin's Q at year $t + 1$ against the natural logarithm of the number of patents filed in year t that are eventually granted. The coefficient for the patent variable thus captures to what extent a firm's technical innovation is incorporated into its market value. In addition, we include in our regression year fixed effects and a set of control variables over year t known to affect Tobin's Q: firm size (measured by the logarithm of sales), research investment (R&D expenditures scaled by total assets), profitability (ROA), capital expenditure (scaled by total assets), leverage (total debt divided by total assets), asset tangibility (net PPE scaled by total assets), industry concentration (measured by the Herfindahl index based on annual sales), and financial constraints (measured by the Kaplan-Zingales (1997) five-variable KZ index).

Next, we define an industry's "Technical Uncertainty" by computing the standard errors of the coefficient for the patent variable for all the firms within an industry, where industry classification is based on the 2-digit SIC codes. The larger the magnitude of an industry's technical uncertainty, the greater the variation of how technological innovations materialize into the value of the firm, thus the greater demand for VC's expertise to effectively monitor an individual firm. Since the industry classification in the Venture Economics database differs from SIC codes in Compustat database, we then use the 2-digit SIC for fraudulent IPOs in our sample to manually match back to our baseline data with the 18-indsutry classification in the Venture Economics database. We define a fraud being occurred in an industry of higher uncertainty (therefore demanding greater VC expertise) if its industry's technical uncertainty is above the median value for the fraud sample. For such kind of firms, VC's expertise contributes to a greater extent in its effective monitoring.

We then re-estimate our results on VC's future exit, VC syndication and underwriter collaboration for subsequent deals based on whether a fraud occurred in an industry of high uncertainty.[19] Table 8 reports the results.

Table 8 reveals that the market "punishes" a VC with monitoring failure where its expertise in monitoring is more important. The marginal effect is larger for frauds that occurred in industries with high uncertainty (Panel A) than with low uncertainty (Panel B), and this economic difference is especially more prominent for IPO exits (-0.431 compared to -0.289) and for VC collaborations with underwriters for future exits (-0.144 compared to -0.047). This result is consistent with Table 3, where the market appears to downward-adjust its perception of VC quality, as the negative impact from VC's monitoring failure persists over a long period of time.[20]

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[19] We cannot conduct our tests for VC's industry concentration and locality. This is because in other tests, the observation unit is VC-portfolio firm; we are able to assign the values of "Technical Uncertainty" to all VCs regardless of whether or not they have previously backed a fraudulent firm (given that it is part of the characteristics of the portfolio firms). By contrast, the observation unit is VC-year in the VC's industry concentration and locality tests; we are unable to assign the value of this variable to VCs who have not backed a fraudulent IPO firm during our sample period.

[20] Our results are not driven by the industry diversification of a VC's portfolio companies and by the hypothesis that monitoring failure is caused by VC's investing into too many different industries instead of the technical uncertainty within an industry demanding more expertise in monitoring. In untabulated regressions, we distinguish between whether a fraud occurred in VCs with investments of a broad and a narrow scope of industries. We do not find there is a difference in the magnitude of setbacks faced by these VCs.

6.3 Fraud Waves

In the light of the wave of corporate financial fraud cases that came to light in the early 2000s, researchers have linked the incidence of fraud with investor beliefs about business conditions (e.g., Hertzberg 2005, Povel, Singh, and Winton 2007, and Kumar and Langberg 2008). In the context of our research setting, it is possible that VCs who fail to provide effective monitoring are blamed less, and thus face less severe consequences, if the IPO fraud occurred during a wave of fraud cases.

We examine whether the market is more tolerant of ineffective VC monitoring when the general business conditions appear to promote more incentive for fraud. We split our sample based on whether the number of fraud cases in the year when the IPO fraud occurred is above or below the sample median, and re-estimate our Table 2 for subsequent exits. In addition to the IPO wave, measured as the number of IPOs at the exit year, we control for fraud waves, measured as the number of fraud cases at the time the IPO fraud occurred.

Table 9 Panel A reports the results with respect to the IPO fraud dummy. The results using Fraud Severity are similar and hence not tabulated. We observe that the dummy for IPO fraud continues to be negatively and significantly linked to subsequent VC exits via IPOs (Columns (1) and (2)), regardless whether or not the IPO fraud was detected during a fraud wave. We find a similar negative relationship when we replace IPO exits with the dummy for successful exit (Columns (3) and (4)), and with the "substitution effect" between the IPO and M&A exits (Columns (5) and (6)).

There is some evidence that the market is more tolerant, and VC takes less blame, if the general business conditions are more prone for the incidence of fraud. Compared to Columns (1), (3) and (5), the marginal effect for the IPO fraud dummy is smaller if the IPO fraud is detected amid a fraud wave (Columns (2), (4) and (6)).

Table 9 Panel B presents the results of industry and geographic concentration for VC's future investments. The dummy for IPO fraud is positively and significantly linked to the degree of industry concentration, and negatively and significantly related to the distance between VC firms and portfolio companies of subsequent VC investments, whether or not the IPO fraud was discovered during a fraud wave. Interestingly, unlike the case of exit, the marginal effect for the IPO fraud dummy is larger during the period of fraud waves than during the non-wave period. This suggests that the limited partners, who are involved with VCs for subsequent investments, do not take a more tolerant approach for ineffective VC monitoring. Instead, they demand even more vigilant VC monitoring.

6.4 Post-Exit Fraud

In Table 3 we find that VCs who fail to provide effective monitoring find it more difficult to exit from their investments in the future, and this negative effect is persistent up to ten years after the fraud was detected. In this subsection, we explore the persistence of the adverse consequence associated with VC's monitoring failure in the context of post-exit fraud. As noted before, the majority of VCs cash out within two years after the IPO. We thus define "Post-Exit Fraud" as a dummy equal to one if the IPO firm backed by a VC committed fraud two years or more after its IPO date.

We investigate whether the VC is still held accountable even when the fraud was committed after VC left the firm. We postulate that a VC suffers less damage in its reputation if fraud occurs after it exits from the fraudulent firm. We re-estimate the baseline regressions in Tables 2, and 4 through 6, replacing the dummy for IPO fraud with the dummy for post-exit fraud. In addition, we include the number of years since the fraudulent firm went public, and its interaction with the dummy for post-exit fraud.

Table 10 reports the results. We observe from Columns (1) through (3) that the dummy for post-exit fraud is significantly linked to a lower probability of IPO exit and a lower probability of a successful exit in subsequent deals. Among successful exits, a post-exit fraud results in a higher likelihood of M&A exits than IPO exits. However, the interaction term between the dummy for post-exit fraud and the number of years since the fraudulent firm's IPO is positive, and is statistically significant for successful exits and IPO vs. M&A exits. This result suggests that while VC still suffers reputational damage even if the fraud occurs after its exit, this negative wealth effect is smaller if a VC exits long before the commitment of fraud.

Columns (4) through (8) of Table 10 reveal that a similar effect exists among financial intermediaries interacting with VCs who suffer reputational damage. While the VC still pays for its monitoring negligence by facing negative consequences when pursuing subsequent investment opportunities, the effect is less pronounced if the exit occurs long before the fraud. These findings suggest that the market holds VC less accountable if a VC is no longer involved with its portfolio companies after the IPO.

6.5 Other Robustness

Since the exact timing of a VC leaving its portfolio firm after taking it public (i.e., when it completes its exit by selling all of its remaining shares or distributing them to limited partners) is unknown, we use the cutoff years identified by Gompers and Lerner (1998) to capture the presence of a VC firm during the fraudulent period of its portfolio company; that is, an IPO fraud is defined as a fraud committed during the period leading up to two years after the IPO. As a robustness check, we re-define IPO fraud as a fraud being committed before or during a portfolio firm's IPO stage, instead of up to two years after the firm going public. Our findings are robust.

In our main analyses, we do not distinguish between VCs who have funded only one and those who have funded more than one fraudulent firm. The 205 fraudulent IPO firms received funding from 196 unique VC firms. Among the 196 VC firms, 38 served as lead VCs, and 20 of them have financed more than one fraudulent firm during our sample period. To ensure that our findings are not driven only by VCs who have funded multiple fraudulent firms, we remove these lead VCs and their portfolio firms from our sample, and re-run Tables 2 through 7. We find statistically and economically similar results. For example, compared to Table 2 Panel A Column (1), the marginal effect associated with the dummy for IPO fraud in predicting a portfolio firm's subsequent exit via an IPO is -0.185 and significant at the 1% level. Compared to Table 4 Panel A Column (2), the OLS coefficient for the dummy for IPO fraud in relating to the industry concentration of a VC's subsequent investment is 0.084 and significant at the 1% level.

7. CONCLUSION

Much of the information-based theories of financial intermediation focus on delegated monitoring. However, there is little evidence on how markets discipline financial intermediaries who fail to perform this function.

In this paper, we use the VC market to address this gap in the empirical literature by looking at the economic consequences for VC firms that fail in their monitoring activity to prevent fraud by their portfolio firms. We find that VCs who fail to prevent fraud have more difficulty in taking future portfolio firms public, and they are more likely to substitute for the most profitable exit—the IPO—with a much less profitable exit—an M&A. More importantly, the diminished opportunity to exit with an IPO exit persists more than ten years after the revelation of the IPO fraud.

We also find that reputation-damaged VCs suffer pressure from their peers, as they interact differently in subsequent deals with their limited partners, other VCs in the community, and underwriters because they are perceived by these groups as inefficient monitors. This peer pressure forces them to follow a more conservative investment strategy, team up with less reputable VC firms in their subsequent deals, and work with less reputable underwriters in future IPOs.

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Table 1: Summary Statistics

Panel A reports the summary statistics for portfolio firms that are backed by VCs and for VC firms from 1995 to 2008. Data about entrepreneurial firms and VC investors are obtained from the Venture Economics database. Variables are defined in the text. Statistics for Industry concentration, physical distance between VCs and entrepreneurial firms, VC age, capital under management, and VC reputations score are based on VC-year observations. Panel B reports the summary statistics for VC-backed IPO firms that committed fraud between 1995 and 2005. Panel C reports the univariate comparisons between VCs that have funded fraudulent IPO firms during the sample period and those that have not. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Characteristics of VCs and Their Portfolio Firms

	Mean	Std. Dev.	# of obs.
Characteristics of VC Firms			
% of VCs that have funded fraudulent IPO firms	11.07		1,770
% of VCs that have funded post-exit fraudulent firms	8.70		1,770
Three-day CAR around the discovery of fraud (%)	-31.61	26.93	171
Industry concentration	0.55	0.30	9,971
Distance between VCs and entrepreneurial firms	214.30	198.32	8,392
VC age	13.56	13.38	9,323
Capital under management ($ million)	29.16	197.94	9,973
VC reputation score (%)			
Based on three-year rolling window	0.10	0.27	5,756
Based on extended window	0.10	0.23	5,756
Characteristics of VC-backed Entrepreneurial Firms			
% of firms going public	9.61		11,500
% of firms going public or being acquired	65.21		11,500
% of firms going public instead of being acquired	14.75		7,500
% of firms receives 1st VC investment at its			
Seed stage	9.02		11,500
Early stage	16.61		11,500
Expansion stage	27.98		11,500
Late stage	2.89		11,500
Buyout stage	6.94		11,500
Other stage	36.56		11,500
# of investing VC firms in the syndicate	3.28	1.84	11,500

Panel B: Characteristics of VC-backed Fraudulent IPOs

	Mean	Std. Dev.	# of obs.
# of investing VCs in a fraudulent firm	6.88	4.63	205
# of financing rounds a fraudulent firm received	4.66	2.44	205
Firm age at the 1st round VC financing	4.42	4.02	189
% of fraudulent firms receives 1st VC investment at its			
Seed stage	30.67		205
Early stage	35.33		205
Expansion stage	22.00		205
Late stage	4.67		205
Buyout stage	6.00		205
Other stage	1.33		205

Panel C: Univariate Comparisons

	VCs that have backed fraudulent IPOs	VCs that have not backed fraudulent IPOs	Difference
VC age	7.21	6.05	1.16
Capital under management ($ billion)	1.625	0.953	0.672
# of firms VC has invested	84.08	31.74	52.34***
# of rounds VC has invested	167.35	58.30	109.05***
Amount VC has invested ($ million)	884.30	337.77	546.54***
VC reputation score (%)			
Based on three-year rolling window	0.12	0.02	0.10***
Based on extended window	0.13	0.02	0.10***
% of California VCs	32.65	20.08	12.58***
% of Massachusetts VCs	17.29	7.24	7.04***
% of New York VCs	15.06	15.88	-0.06
# of obs.	196	1,574	

Table 2: Exit Outcomes

This table reports the regressions for the exit outcomes of VC firms. Panel A reports the probit regression results for the exit outcomes of VC's portfolio firms. Panel B reports the linear probability regression results for the exit outcomes of VC's portfolio firms. The dependent variable in columns (1) and (2) are the IPO exit dummy that equals one if the VC firm exits via IPO and zero otherwise. The dependent variable in columns (3) and (4) are the Successful Exit dummy that equals one if the VC firm exits through either IPO or M&A and zero otherwise. The dependent variable in columns (5) and (6) are the IPO vs. M&A dummy that equals one if the VC firm exits via IPO and zero if the VC firm exits via M&A. The independent variables include the IPO fraud dummy, fraud severity, as well as control variables of IPO wave (the number of IPOs in the year), the seed stage dummy, the early stage dummy, the expansion stage dummy, the late stage dummy, VC firm's age, natural logarithm of capital under VC firm's management. In Panel A the probit regression also includes entrepreneurial firm's industry fixed effects. In Panel B, the linear probability model includes VC firm's fixed effects in addition to entrepreneurial firm's industry fixed effects. Data about entrepreneurial firms and VC investors are obtained from the Venture Economics database. Heteroskedasticity-robust standard errors clustered at the VC firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Probit Model

Dependent Variable	IPO Exit		Successful Exit		IPO vs. M&A	
	(1)	(2)	(3)	(4)	(5)	(6)
IPO fraud dummy	-0.359***		-0.218***		-0.270***	
	(0.086)		(0.054)		(0.045)	
Fraud severity		-0.197***		-0.094***		-0.113***
		(0.063)		(0.008)		(0.022)
IPO wave	0.001***	0.001***	0.001***	0.001***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Seed stage	0.003	-0.034	-0.094**	-0.114***	0.078*	0.068
	(0.067)	(0.081)	(0.045)	(0.019)	(0.046)	(0.052)
Early stage	-0.058	-0.074	-0.063	-0.072***	-0.005	-0.011
	(0.069)	(0.081)	(0.044)	(0.014)	(0.044)	(0.051)
Expansion stage	-0.118*	-0.144*	-0.131***	-0.146***	-0.014	-0.029
	(0.070)	(0.084)	(0.046)	(0.013)	(0.042)	(0.049)
Late stage	-0.117	-0.140	-0.054	-0.070***	-0.060	-0.076
	(0.084)	(0.099)	(0.057)	(0.026)	(0.059)	(0.071)
VC age	0.006**	0.006*	0.004*	0.004***	0.004***	0.004**
	(0.003)	(0.003)	(0.002)	(0.000)	(0.001)	(0.002)
Ln(Capital under	0.027**	0.019*	0.018***	0.014***	0.012***	0.007*
management)	(0.011)	(0.010)	(0.006)	(0.001)	(0.004)	(0.004)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	12,401	12,401	12,401	12,401	7,887	7,887
Pseudo R^2	0.292	0.265	0.132	0.120	0.353	0.332

Table 2 continued.

Panel B: Linear Probability Model						
Dependent Variable	IPO Exit		Successful Exit		IPO vs. M&A	
	(1)	(2)	(3)	(4)	(5)	(6)
IPO fraud dummy	-0.082***		-0.105***		-0.050*	
	(0.018)		(0.022)		(0.029)	
Fraud severity		-0.005		-0.002		-0.005
		(0.036)		(0.054)		(0.046)
IPO wave	0.001***	0.001***	0.000***	0.000***	0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Seed stage	0.110***	0.111***	0.011	0.011	0.195***	0.195***
	(0.019)	(0.020)	(0.021)	(0.023)	(0.024)	(0.028)
Early stage	0.091***	0.089***	0.058***	0.056***	0.113***	0.111***
	(0.014)	(0.014)	(0.016)	(0.016)	(0.019)	(0.021)
Expansion stage	0.046***	0.045***	0.015	0.014	0.053***	0.052***
	(0.012)	(0.014)	(0.015)	(0.016)	(0.017)	(0.019)
Late stage	0.050**	0.050**	0.075***	0.075**	0.033	0.033
	(0.022)	(0.025)	(0.028)	(0.030)	(0.028)	(0.031)
VC age	0.024***	0.021***	0.038***	0.036***	0.001	-0.000
	(0.002)	(0.004)	(0.002)	(0.004)	(0.002)	(0.005)
Ln(Capital under	-0.007	-0.011	-0.050***	-0.056***	0.035***	0.033
management)	(0.007)	(0.010)	(0.009)	(0.011)	(0.010)	(0.025)
Constant	0.077	0.151	0.396***	0.490***	0.293***	0.325
	(0.069)	(0.100)	(0.079)	(0.098)	(0.073)	(0.275)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
VC firm FE	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	12,401	12,401	12,401	12,401	9,710	9,710
Pseudo R^2	0.556	0.555	0.358	0.356	0.613	0.613

Table 3: Persistence of Exit Outcomes

This table reports the probit regressions for the persistence of exit outcomes of VC firms. The dependent variable in Panel A is the IPO exit dummy that equals one if the VC firm exits via IPO and zero otherwise. The dependent variable in Panel B is the Successful Exit dummy that equals one if the VC firm exits through either IPO or M&A and zero otherwise. The dependent variable in Panel C is the IPO vs. M&A dummy that equals one if the VC firm exits via IPO and zero if the VC firm exits via M&A. The independent variables include the IPO fraud dummy, fraud severity, and a set of control variables (untabulated): IPO wave (the number of IPOs in the year), the seed stage dummy, the early stage dummy, the expansion stage dummy, the late stage dummy, VC firm's age at the time of exit, natural logarithm of capital under VC firm's management at the time of exit. In addition, we control for entrepreneurial firm's industry fixed effects. Data about entrepreneurial firms and VC investors are obtained from the Venture Economics database. Heteroskedasticity-robust standard errors clustered at the VC firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: IPO Exit

	Year t	Year t+1	Year t+3	Year t+5	Year t+10	Year t	Year t+1	Year t+3	Year t+5	Year t+10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IPO fraud dummy	-0.378***	-0.361***	-0.372***	-0.370***	-0.377***					
	(0.087)	(0.087)	(0.085)	(0.087)	(0.087)					
Fraud severity						-0.220***	-0.201***	-0.216***	-0.218***	-0.219***
						(0.063)	(0.062)	(0.063)	(0.063)	(0.062)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	11,057	11,622	11,424	11,239	11,066	11,057	11,622	11,424	11,239	11,066
Pseudo R^2	0.307	0.295	0.307	0.299	0.307	0.289	0.274	0.286	0.281	0.289

Table 3 continued.

Panel B: Successful Exit

	Year t	Year t+1	Year t+3	Year t+5	Year t+10	Year t	Year t+1	Year t+3	Year t+5	Year t+10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IPO fraud dummy	-0.248***	-0.235***	-0.225***	-0.244***	-0.248***					
	(0.055)	(0.055)	(0.053)	(0.056)	(0.055)					
Fraud severity						-0.104***	-0.103***	-0.095***	-0.102***	-0.104***
						(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	11,057	11,622	11,424	11,239	11,066	11,057	11,622	11,424	11,239	11,066
Pseudo R^2	0.155	0.144	0.147	0.149	0.155	0.145	0.133	0.137	0.137	0.145

Panel C: IPO vs. M&A

	Year t	Year t+1	Year t+3	Year t+5	Year t+10	Year t	Year t+1	Year t+3	Year t+5	Year t+10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IPO fraud dummy	-0.272***	-0.250***	-0.280***	-0.253***	-0.270***					
	(0.050)	(0.046)	(0.046)	(0.047)	(0.050)					
Fraud severity						-0.110***	-0.102***	-0.117***	-0.112***	-0.109***
						(0.022)	(0.021)	(0.022)	(0.022)	(0.022)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	7,223	7,496	7,411	7,330	7,226	7,223	7,496	7,411	7,330	7,226
Pseudo R^2	0.351	0.347	0.356	0.348	0.351	0.337	0.331	0.340	0.336	0.337

Table 4: VC Investment Concentrations

This table reports the regressions for the industry concentration and locality of VC firms. The dependent variable in Panel A is the VC firm's industry concentration measured by its investment Herfindahl index based on the Venture Economics 18-industry classifications. The dependent variable in Panel B is the VC firm's investment locality measured by the natural logarithm of the physical distance between the VC firm and its portfolio firms. The independent variables include the IPO fraud dummy, fraud severity, VC age, natural logarithm of capital under management, VC firm's prior performance, VC firm dummies, and year dummies. Data about entrepreneurial firms and VC investors are obtained from the Venture Economics database. Heteroskedasticity-robust standard errors clustered at the VC firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Industry Concentration

Dependent Variable	Industry Concentration	
	(1)	(2)
IPO fraud dummy	0.082***	
	(0.016)	
Fraud severity		0.018**
		(0.008)
VC age	-0.011***	-0.010***
	(0.001)	(0.001)
Ln(Capital under management)	-0.272***	-0.282***
	(0.104)	(0.107)
VC's prior performance	-0.025**	-0.026**
	(0.011)	(0.011)
Constant	0.716***	0.718***
	(0.020)	(0.021)
VC FE	Yes	Yes
Year FE	Yes	Yes
# of obs.	9,971	9,971
R^2	0.619	0.618

Table 4 continued.

Panel B: Locality

Dependent Variable	Ln(Distance)		% of Local Investment	
	(1)	(2)	(3)	(4)
IPO fraud dummy	-0.151**		0.044**	
	(0.071)		(0.021)	
Fraud severity		-0.077**		0.021**
		(0.036)		(0.010)
VC age	0.000	0.001	-0.004**	-0.004**
	(0.007)	(0.007)	(0.002)	(0.002)
Ln(Capital under management)	0.725***	0.742***	-0.061	-0.070
	(0.189)	(0.197)	(0.054)	(0.057)
VC's prior performance	-0.092	-0.091	0.016	0.015
	(0.065)	(0.065)	(0.016)	(0.016)
Constant	4.683***	4.662***	0.414***	0.420***
	(0.097)	(0.099)	(0.027)	(0.027)
VC FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
# of obs.	8,956	8,956	8,956	8,956
R^2	0.416	0.416	0.476	0.476

Table 5: VC Syndication

This table reports the regressions for the syndication of VC firms. The dependent variable in Panel A is the natural logarithm of the number of VC firms in a syndicate. The dependent variable in Panel B is the high VC Reputation (Rolling) dummy that equals one if the weighted average reputation of other VCs in a syndicate is higher or equal to the VC firm's own reputation when VC reputation is calculated based on a rolling window, and zero otherwise. The dependent variable in Panel C is the high VC Reputation (Extended) dummy that equals one if the weighted average reputation of other VCs in a syndicate is higher or equal to the VC firm's own reputation when VC reputation is calculated based on an extended window since 1980, and zero otherwise. The independent variables include the IPO fraud dummy, fraud severity, VC age, natural logarithm of capital under management, VC firm's prior performance, VC firm dummies, and year dummies. Data about entrepreneurial firms and VC investors are obtained from the Venture Economics database. Heteroskedasticity-robust standard errors clustered at the VC firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel A		**Panel B**		**Panel C**	
Dependent Variable	Ln(# of VCs)		High VC Reputation (Rolling)		High VC Reputation (Extended)	
	(1)	(2)	(3)	(4)	(5)	(6)
IPO fraud dummy	-0.089***		-0.259***		-0.271***	
	(0.030)		(0.053)		(0.056)	
Fraud severity		-0.024*		-0.092***		-0.097***
		(0.014)		(0.022)		(0.025)
VC age	-0.027***	-0.027***	-0.002***	-0.002**	-0.003***	-0.002***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Capital under management)	-0.069	-0.058	-0.009**	-0.013***	-0.005	-0.009*
	(0.072)	(0.075)	(0.004)	(0.004)	(0.004)	(0.005)
VC's prior performance	0.006	0.007	0.027**	0.034**	0.040***	0.048***
	(0.021)	(0.021)	(0.014)	(0.016)	(0.015)	(0.017)
Constant	2.238***	2.233***				
	(0.040)	(0.041)				
VC FE	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes
# of obs.	9,926	9,926	16,042	16,042	16,055	16,055
(Pseudo) R^2	0.439	0.438	0.154	0.144	0.134	0.124

Table 6: Underwriter Reputation

This table reports the regressions for the underwriter reputation of IPO firms backed by VC firms. The dependent variable in Panel A is the average reputation of underwriter syndicate of IPO firms backed by VC firms. The dependent variable in Panel B is the high IB Reputation dummy that equals one if the reputation of underwriter syndicate for the current IPO firm backed by the VC firm is higher than that of underwriter syndicate for the previous IPO backed by the same VC firm and zero otherwise. The independent variables include the IPO fraud dummy, fraud severity, VC age, natural logarithm of capital under management, VC firm's prior performance, VC firm dummies, and year dummies. Data about entrepreneurial firms and VC investors are obtained from the Venture Economics database. Heteroskedasticity-robust standard errors clustered at the VC firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Panel A		**Panel B**	
Dependent Variable	IB Reputation		High IB Reputation	
	(1)	(2)	(3)	(4)
IPO fraud dummy	-0.159***		-0.054***	
	(0.057)		(0.019)	
Fraud severity		-0.093***		-0.037***
		(0.036)		(0.013)
VC age	0.036***	0.029***	-0.002***	-0.002*
	(0.012)	(0.006)	(0.000)	(0.001)
Ln(Capital under management)	-0.026	-0.140***	-0.020***	-0.020***
	(0.033)	(0.028)	(0.002)	(0.004)
VC's prior performance	0.035	0.057	-0.004	-0.008
	(0.075)	(0.090)	(0.028)	(0.033)
Constant	7.119***	7.959***		
	(0.320)	(0.266)		
VC FE	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes
# of obs.	5,882	5,584	5,859	5,563
(Pseudo) R^2	0.314	0.291	0.101	0.102

Table 7: Early versus Late Stage VCs

This table reports the regressions to examine the effect of fraud for early stage and late state VCs. The dependent variables are the IPO exit dummy that equals one if the VC firm exits via IPO and zero otherwise, the Successful Exit dummy that equals one if the VC firm exits through either IPO or M&A and zero otherwise, the IPO Vs. M&A dummy that equals one if the VC firm exits via IPO and zero if the VC firm exits via M&A, the VC firm's industry concentration measured by its investment Herfindahl index based on the Venture Economics 18-industry classifications, the VC firm's investment locality measured by the natural logarithm of the physical distance between the VC firm and its portfolio firms, the natural logarithm of the number of VC firms in a syndicate, the high VC Reputation dummy that equals one if the weighted average reputation of other VCs in a syndicate is higher or equal to the VC firm's own reputation when VC reputation is calculated based on a rolling window and zero otherwise, and the high IB Reputation dummy that equals one if the reputation of underwriter syndicate for the current IPO firm backed by the VC firm is higher than that of underwriter syndicate for the previous IPO backed by the same VC firm and zero otherwise, respectively. The independent variables include the IPO fraud dummy and a set of control variables (untabulated). For columns (1) through (3), the control variables are: IPO wave (the number of IPOs in the year), the seed stage dummy, the early stage dummy, the expansion stage dummy, the late stage dummy, VC firm's age at the time of exit, and natural logarithm of capital under VC firm's management at the time of exit. For columns (4) through (8), the control variables are: VC age, natural logarithm of capital under management, and VC firm's prior performance. Panel A report regressions for early-stage VC firms, and Panel B report regressions results for late-stage VC firms. Data about entrepreneurial firms and VC investors are obtained from the Venture Economics database. Heteroskedasticity-robust standard errors clustered at the VC firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: VCs That Invested in Firms at Early Stage

Dependent Variable	IPO Exit	Successful Exit	IPO vs. M&A	Industry Concentration	Distance	Ln(# of VCs)	High VC Reputation	High IB Reputation
	Probit	Probit	Probit	OLS	OLS	OLS	Probit	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IPO fraud dummy	-0.460***	-0.255***	-0.166***	0.086***	-0.205**	-0.100***	-0.206***	-0.086***
	(0.089)	(0.092)	(0.051)	(0.018)	(0.086)	(0.034)	(0.034)	(0.032)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	No	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes	Yes	Yes
VC FE	No	No	No	Yes	Yes	Yes	No	No
# of obs.	7,659	7,659	4,080	6,895	6,209	6,874	8,166	4,961
(Pseudo) R^2	0.435	0.275	0.344	0.652	0.485	0.483	0.120	0.039

Panel B: VCs That Invested in Firms at Late Stage

Dependent Variable	IPO Exit	Successful Exit	IPO vs. M&A	Industry Concentration	Distance	Ln(# of VCs)	High VC Reputation	High IB Reputation
	Probit	Probit	Probit	OLS	OLS	OLS	Probit	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IPO fraud dummy	-0.045	-0.040	-0.053	0.027	-0.091	-0.041	-0.100***	0.022
	(0.028)	(0.026)	(-0.040)	(0.038)	(0.254)	(0.078)	(0.047)	(0.043)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	No	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes	Yes	Yes
VC FE	No	No	No	Yes	Yes	Yes	No	No
# of obs.	4,742	4,742	3,807	3,076	2,747	3,052	4,785	1,573
(Pseudo) R^2	0.089	0.018	0.187	0.757	0.567	0.655	0.307	0.023

Table 8 Monitoring Failure and the Lack of Expertise

This table reports the regressions to examine the effect of the demand of VC expertise in order to perform monitoring role. The dependent variables are the IPO exit dummy that equals one if the VC firm exits via IPO and zero otherwise, the Successful Exit dummy that equals one if the VC firm exits through either IPO or M&A and zero otherwise, the IPO Vs. M&A dummy that equals one if the VC firm exits via IPO and zero if the VC firm exits via M&A, the natural logarithm of the number of VC firms in a syndicate, and the high IB Reputation dummy that equals one if the reputation of underwriter syndicate for the current IPO firm backed by the VC firm is higher than that of underwriter syndicate for the previous IPO backed by the same VC firm and zero otherwise, respectively. The independent variables include the IPO fraud dummy and a set of control variables (untabulated). For columns (1) through (3), the control variables are: IPO wave (the number of IPOs in the year), the seed stage dummy, the early stage dummy, the expansion stage dummy, the late stage dummy, VC firm's age at the time of exit, and natural logarithm of capital under VC firm's management at the time of exit. For columns (4) and (5), the control variables are: VC age, natural logarithm of capital under management, and VC firm's prior performance. Panel A report regressions for VC firms who backed a fraudulent firm in an industry of high uncertainty, and Panel B report regressions results for VC firms who backed a fraudulent firm in an industry of low uncertainty. Data about entrepreneurial firms and VC investors are obtained from the Venture Economics database. Heteroskedasticity-robust standard errors clustered at the VC firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Fraudulent IPOs in More Uncertain Industries

Dependent Variable	IPO Exit	Successful Exit	IPO vs. M&A	High VC Reputation	High IB Reputation
	(1)	(2)	(3)	(4)	(5)
IPO fraud dummy	-0.431***	-0.232***	-0.319***	-0.320***	-0.144***
	(0.086)	(0.049)	(0.046)	(0.054)	(0.046)
Control variables	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes
VC FE	No	No	No	No	No
# of obs.	6,924	6,924	4,719	7.095	1,129
(Pseudo) R^2	0.349	0.154	0.420	0.160	0.161

Table 8 continued.

Panel B: Fraudulent IPOs in Less Uncertain Industries

Dependent Variable	IPO Exit	Successful Exit	IPO vs. M&A	High VC Reputation	High IB Reputation
	(1)	(2)	(3)	(4)	(5)
IPO fraud dummy	-0.289***	-0.214***	-0.228***	-0.257***	-0.047**
	(0.079)	(0.026)	(0.062)	(0.061)	(0.021)
Control variables	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes
VC FE	No	No	No	No	No
# of obs.	1,492	1,492	867	4,109	4,538
(Pseudo) R^2	0.187	0.084	0.227	0.109	0.090

Table 9: Fraud Waves

This table reports the regressions to examine the effect of fraud waves. The dependent variables in Panel A are the IPO exit dummy that equals one if the VC firm exits via IPO and zero otherwise, the Successful Exit dummy that equals one if the VC firm exits through either IPO or M&A and zero otherwise, and the IPO Vs. M&A dummy that equals one if the VC firm exits via IPO and zero if the VC firm exits via M&A, respectively. The independent variables include the IPO fraud dummy, fraud severity, the number of IPOs in the year, the seed stage dummy, the early stage dummy, the expansion stage dummy, the late stage dummy, and entrepreneurial firm's industry dummies. The dependent variables in Panel B are the VC firm's industry concentration measured by its investment Herfindahl index based on the Venture Economics 18-industry classifications and the VC firm's investment locality measured by the natural logarithm of the physical distance between the VC firm and its portfolio firms, respectively. The independent variables include the IPO fraud dummy, fraud severity, VC age, natural logarithm of capital under management, VC firm's prior performance, VC firm dummies, and year dummies. Data about entrepreneurial firms and VC investors are obtained from the Venture Economics database. Heteroskedasticity-robust standard errors clustered at the VC firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Exit Outcomes

Dependent Variable	IPO Exit		Successful Exit		IPO vs. M&A	
	# of fraud < median	# of fraud > median	# of fraud < median	# of fraud > median	# of fraud < median	# of fraud > median
	(1)	(2)	(3)	(4)	(5)	(6)
IPO fraud	-0.306***	-0.260***	-0.183***	-0.167***	-0.270***	-0.183***
	(0.085)	(0.081)	(0.061)	(0.047)	(0.088)	(0.059)
No of fraud in the year	0.013***	0.001	-0.001	0.019***	0.003	-0.000
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
IPO wave	0.001***	0.001***	0.001***	0.000**	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Seed stage	0.004	-0.062	-0.130**	-0.044	0.076	0.036
	(0.084)	(0.081)	(0.062)	(0.046)	(0.052)	(0.040)
Early stage	-0.101	-0.050	-0.031	-0.078*	-0.024	-0.014
	(0.084)	(0.080)	(0.056)	(0.045)	(0.061)	(0.044)
Expansion stage	-0.088	-0.173**	-0.171***	-0.071	-0.071	-0.008
	(0.078)	(0.085)	(0.064)	(0.045)	(0.067)	(0.037)
Late stage	-0.057	-0.179*	-0.137*	0.086*	-0.151	-0.073
	(0.104)	(0.094)	(0.074)	(0.048)	(0.093)	(0.063)
VC age	0.005*	0.004	0.003	0.002	0.003	0.003**
	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)
Ln(Capital under	0.018**	0.020*	0.013*	0.009**	0.013*	0.006
management)	(0.009)	(0.011)	(0.007)	(0.005)	(0.007)	(0.004)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
# of obs.	5,601	6,050	5,601	6,050	3,262	4,188
Pseudo R^2	0.225	0.355	0.095	0.231	0.311	0.369

Table 9 continued.

Panel B: Industry Concentration and Locality

Dependent Variable	Industry Concentration		Ln(Distance)	
	# of fraud < median	# of fraud > median	# of fraud < median	# of fraud > median
	(1)	(2)	(3)	(4)
IPO fraud	0.080***	0.089***	-0.193*	-0.269**
	(0.022)	(0.022)	(0.115)	(0.109)
VC age	-0.011***	-0.010***	-0.047	-0.034
	(0.002)	(0.002)	(0.057)	(0.066)
Ln(Capital under management)	-0.288**	-0.233**	1.120**	0.865***
	(0.128)	(0.105)	(0.459)	(0.322)
VC's prior performance	-0.064***	0.009	-0.111	-0.081
	(0.016)	(0.021)	(0.103)	(0.129)
Constant	0.691***	0.702***	4.813***	4.835***
	(0.024)	(0.024)	(0.124)	(0.149)
VC FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
# of obs.	5,014	4,957	5,081	4,381
R^2	0.681	0.672	0.489	0.531

Table 10: Post-Exit Fraud

This table reports the regressions to post-exit fraud. The dependent variables are the IPO exit dummy that equals one if the VC firm exits via IPO and zero otherwise, the Successful Exit dummy that equals one if the VC firm exits through either IPO or M&A and zero otherwise, the IPO Vs. M&A dummy that equals one if the VC firm exits via IPO and zero if the VC firm exits via M&A, the VC firm's industry concentration measured by its investment Herfindahl index based on the Venture Economics 18-industry classifications, the VC firm's investment locality measured by the natural logarithm of the physical distance between the VC firm and its portfolio firms, the natural logarithm of the number of VC firms in a syndicate, the high VC Reputation dummy that equals one if the weighted average reputation of other VCs in a syndicate is higher or equal to the VC firm's own reputation when VC reputation is calculated based on a rolling window and zero otherwise, and the high IB Reputation dummy that equals one if the reputation of underwriter syndicate for the current IPO firm backed by the VC firm is higher than that of underwriter syndicate for the previous IPO backed by the same VC firm and zero otherwise, respectively. The independent variables include the post-exit fraud dummy and a set of control variables (untabulated). For columns (1) through (3), the control variables are: IPO wave (the number of IPOs in the year), the seed stage dummy, the early stage dummy, the expansion stage dummy, the late stage dummy, VC firm's age at the time of exit, and natural logarithm of capital under VC firm's management at the time of exit. For columns (4) through (8), the control variables are: VC age, natural logarithm of capital under management, and VC firm's prior performance. Data about entrepreneurial firms and VC investors are obtained from the Venture Economics database. Heteroskedasticity-robust standard errors clustered at the VC firm level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 10 continued.

Dependent Variable	IPO Exit	Successful Exit	IPO vs. M&A	Industry Concentration	Locality	Ln(# of VCs)	High VC Reputation	High IB Reputation
	Probit	Probit	Probit	OLS	OLS	OLS	Probit	Probit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post-Exit fraud dummy	-0.482***	-0.635***	-0.830***	0.053***	-0.118*	-0.055**	-0.190***	-0.462*
	(0.073)	(0.064)	(0.060)	(0.014)	(0.070)	(0.026)	(0.048)	(0.098)
# of years since IPO	-0.031	-0.006	-0.123***	0.005**	-0.002	-0.008	-0.005	-0.086***
	(0.021)	(0.016)	(0.052)	(0.002)	(0.019)	(0.007)	(0.007)	(0.020)
Post-Exit fraud dummy×#	0.011	0.030*	0.125***	-0.006**	0.004	0.009	0.042**	0.236***
of years since IPO	(0.021)	(0.018)	(0.055)	(0.002)	(0.019)	(0.007)	(0.019)	(0.090)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	No	Yes	Yes
Year FE	No	No	No	Yes	Yes	Yes	Yes	Yes
VC FE	No	No	No	Yes	Yes	Yes	No	No
# of obs.	12,401	12,401	7,887	9,971	8,956	9.926	16,055	6,570
(Pseudo) R^2	0.251	0.112	0.320	0.619	0.416	0.438	0.115	0.038